SMART CITIES AS CYBER-PHYSICAL SYSTEMS

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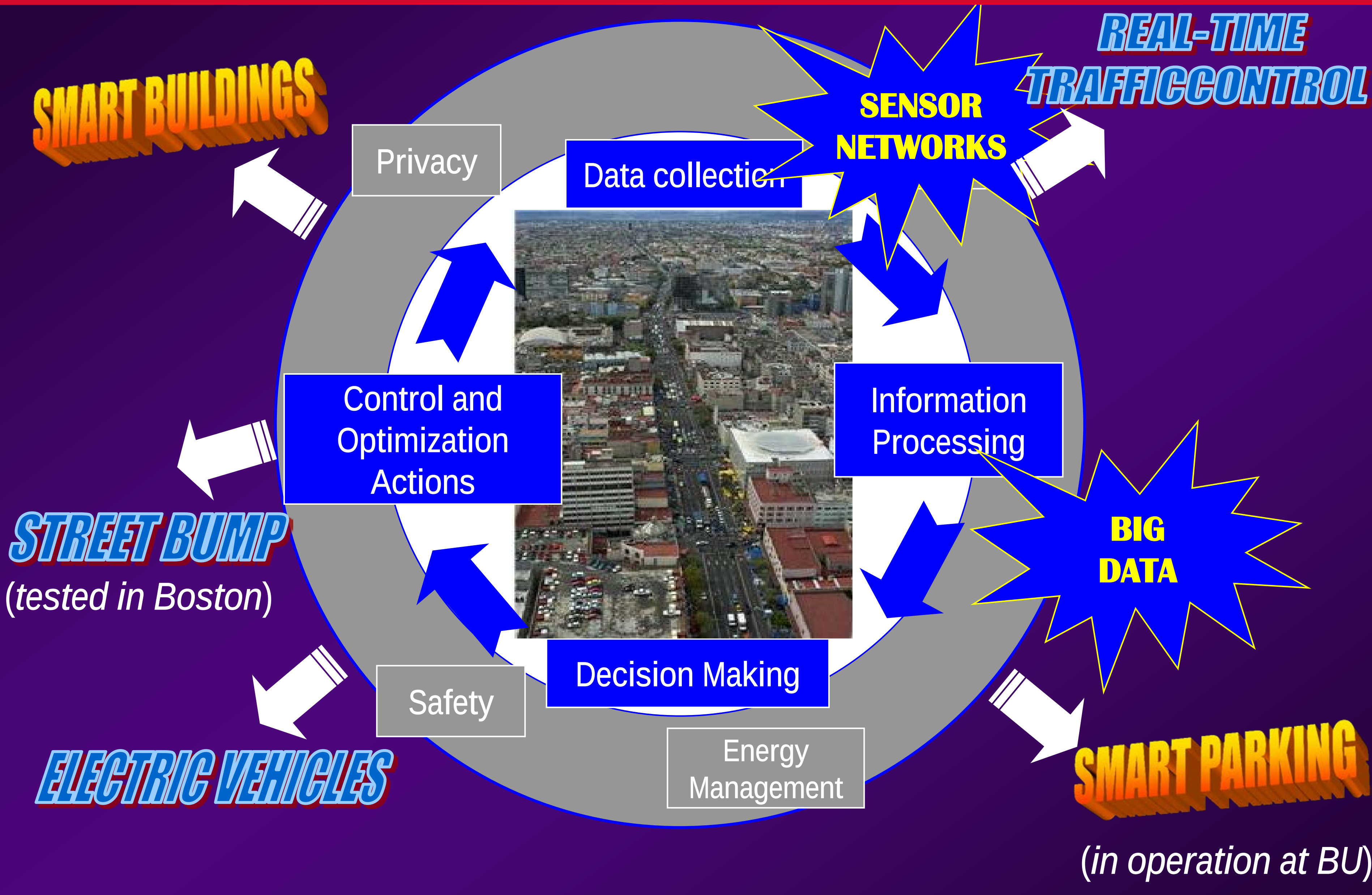
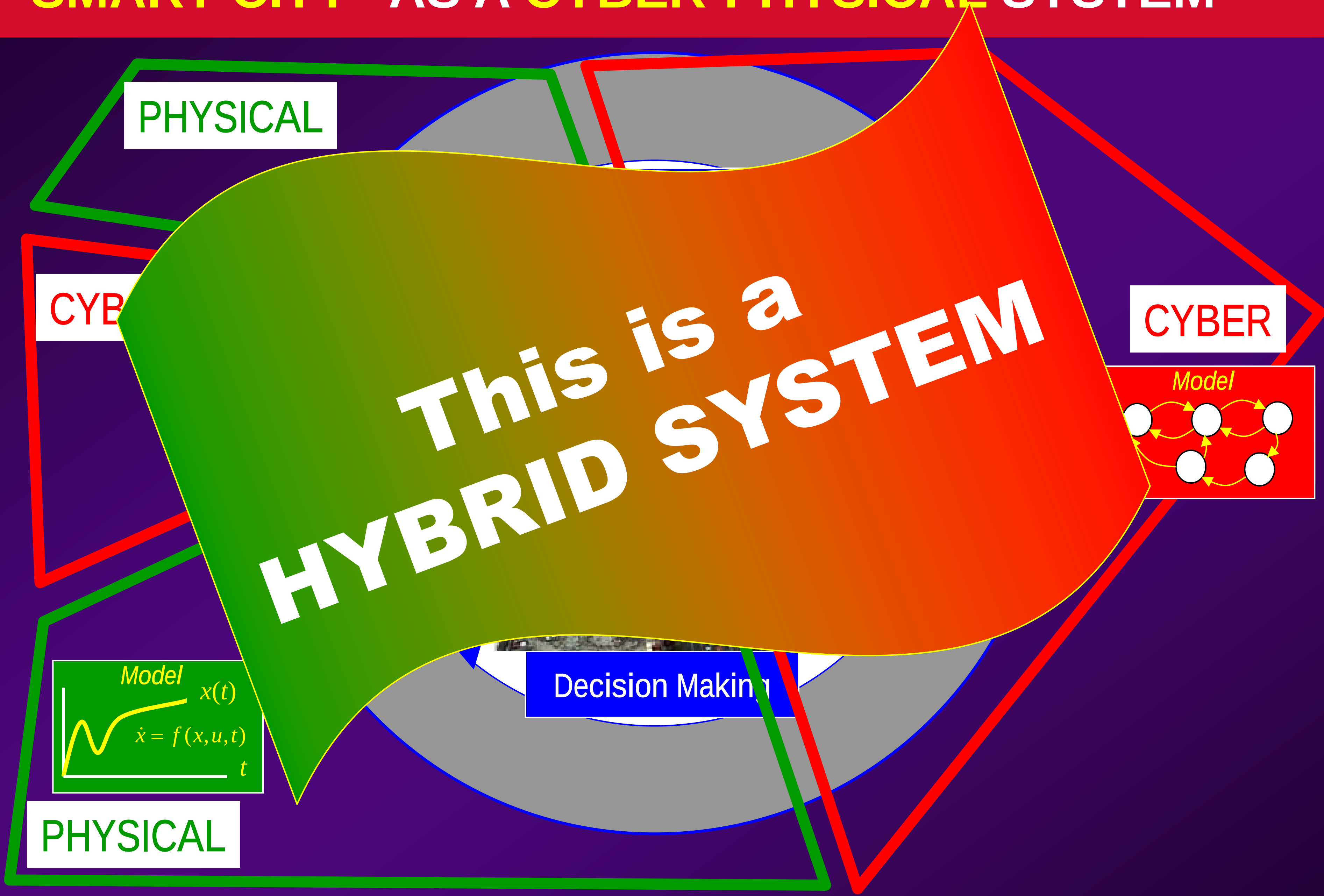
OUTLINE

- What is a "Smart City" ?
- A Data-Driven Dynamic Resource Allocation Framework
- Control and Optimization in Smart Cities:
  - Adaptive Traffic Light Control
  - Smart Parking
  - Energy-aware Traffic Management
  - Street Bump
  - Social aspects (incentives, selfish v. social behavior)

“SMART CITY” AS A CYBER-PHYSICAL SYSTEM



“SMART CITY” AS A CYBER-PHYSICAL SYSTEM



WHAT IS A "SMART CITY" ?

"A city well performing in a forward-looking way in [economy, people, governance, mobility, environment, and living] built on the smart combination of endowments and activities of self-decisive, independent and aware citizens." *Giffinger et al, 2007*

Smart Sustainable Cities use information and communication technologies (ICT) to be more intelligent and efficient in the use of resources, resulting in cost and energy savings, improved service delivery and quality of life, and reduced environmental footprint--all supporting innovation and the low-carbon economy. *Cohen, 2014*

Hitachi's vision for the Smart Sustainable City seeks to achieve concern for the global environment and lifestyle safety and convenience through the coordination of infrastructure. Smart Sustainable Cities realized through the coordination of infrastructures consist of two infrastructure layers that support consumers' lifestyles together with the urban management infrastructure that links these together using IT *Hitachi Web, 2014*

"We believe a city to be smart when investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance." *Meijer and Bolívar, 2013*

WHAT IS A “SMART CITY” ?

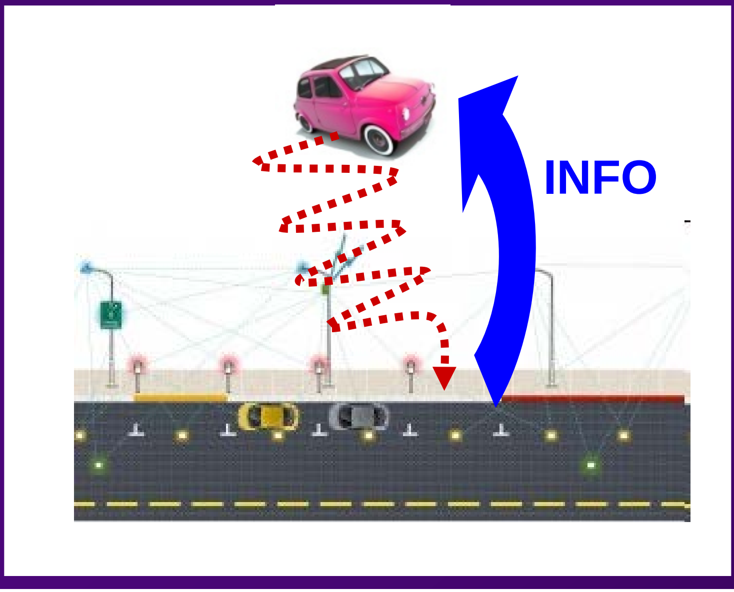
CREDIT: Fernando Livschitz

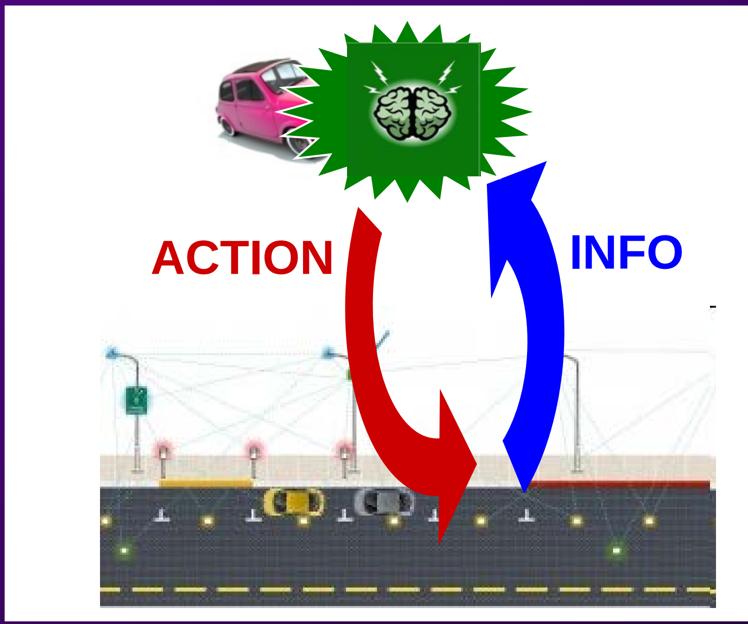
http://www.fastcodesign.com/3035870/filmmaker-creates-worlds-most-terrifying-traffic-intersection

WHAT IS *REALLY* "SMART" ?

COLLECTING DATA IS NOT "SMART"

- JUST A NECESSARY STEP TO BEING "SMART"





PROCESSING DATA TO MAKE GOOD DECISIONS IS "SMART"

WHAT IS A "SMART CITY" ?

- Ubiquitous wireless connectivity of *resources* and *users*

- Sharing real-time state information among *users* and *resources*
  ⇒ feedback control mechanisms

- Sharing real-time state information among *users* and *resources*
  ⇒ reduce/eliminate much of the infrastructure
  (e.g., *Automated Vehicles in urban networks, Virtual Traffic Lights*)

- Game viewpoint in sharing resources: when player lacks information about the behavior of other players, poor decisions are made
  ⇒ user-centric (selfish) vs system-centric (socially optimal) decisions

- Data-driven control and optimization methodologies

DATA-DRIVEN DYNAMIC RESOURCE ALLOCATION

DYNAMIC RESOURCE ALLOCATION

CHARGING STATIONS

TRAFFIC LIGHTS

ZIPCARS

STATE $\mathbf{x}(t)$

TIME

$$\mathbf{x}(t') = f[\mathbf{x}(t), \mathbf{u}(t), e(t)], \quad t' > t$$

CONTROL

- Reserve resource
- De-assign resource
- Change resource price
- Steer vehicle
- …

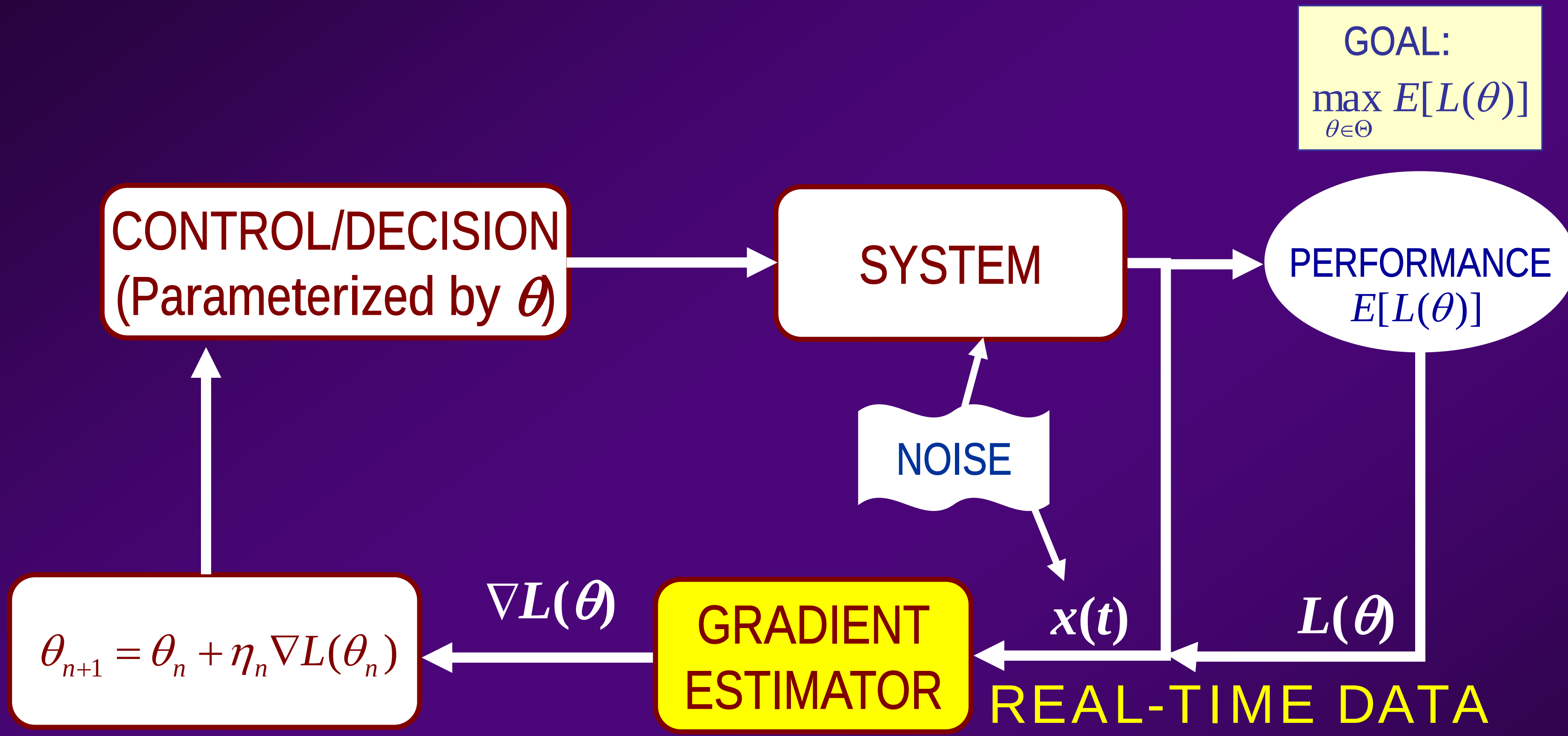
$$\min_{\mathbf{u}(t)} J(x(t), \mathbf{u}(t), t)$$

$$\text{s.t.} \begin{cases} \text{user constraints} \\ \text{resource constraints} \end{cases}$$

EVENTS

- New request
- Cancel request
- Resource freed
- …

DATA-DRIVEN STOCHASTIC OPTIMIZATION

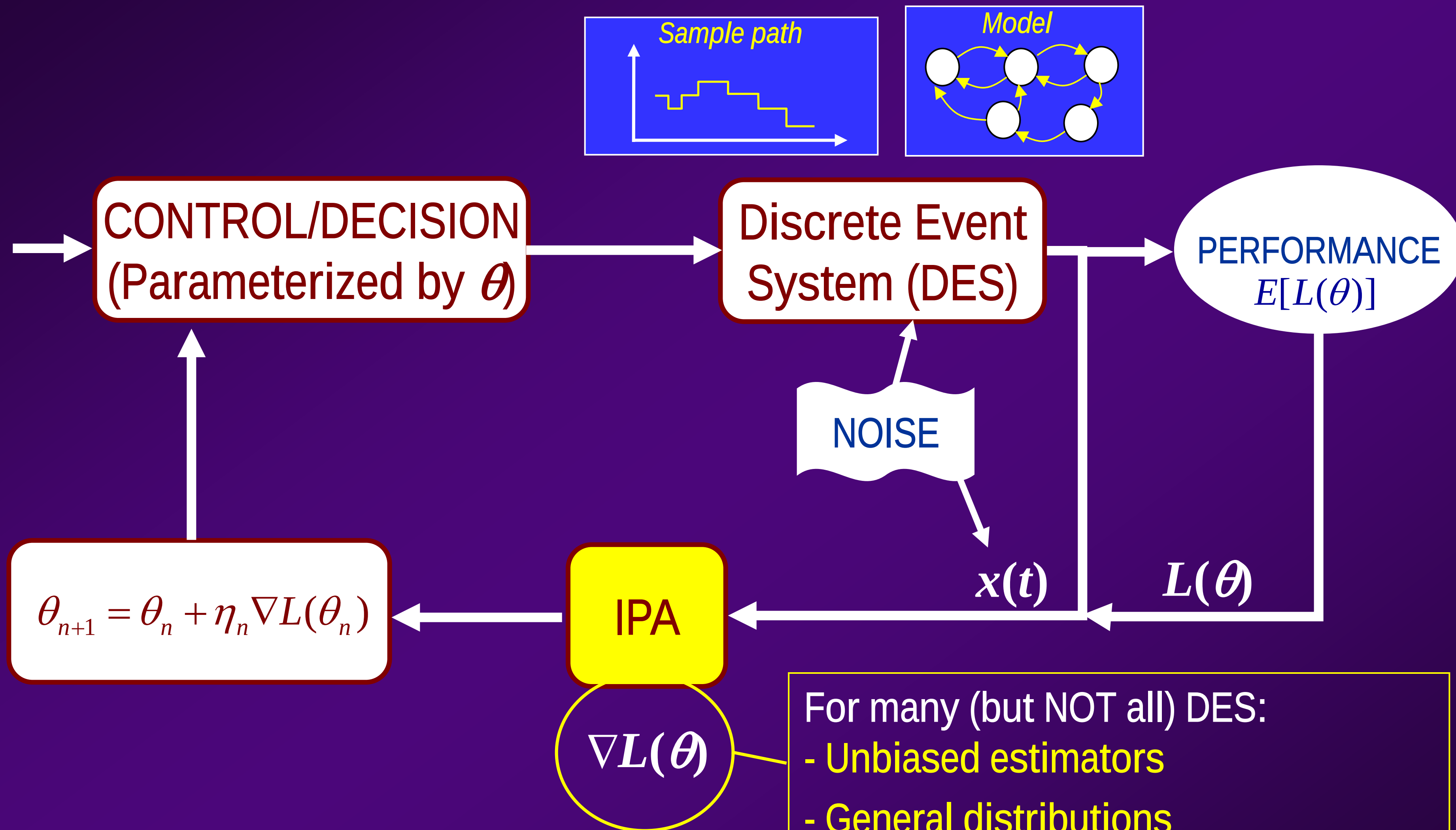


DIFFICULTIES: - $E[L(\theta)]$ NOT available in closed form

- $\nabla L(\theta)$ not easy to evaluate

- $\nabla L(\theta)$ may not be a good estimate of $\nabla E[L(\theta)]$

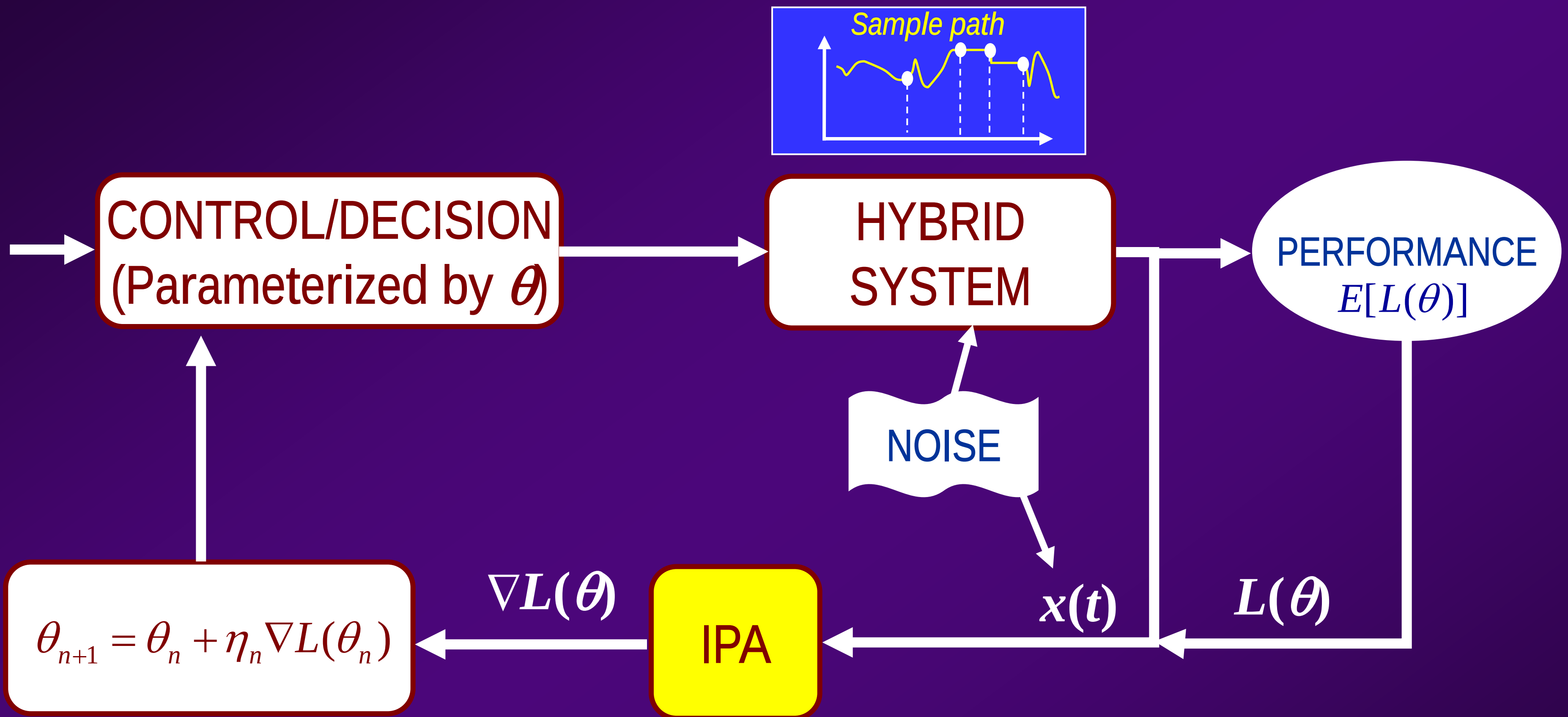
DATA-DRIVEN STOCHASTIC OPTIMIZATION IN *DES*: INFINITESIMAL PERTURBATION ANALYSIS (IPA)



For many (but NOT all) DES:
- Unbiased estimators
- General distributions
- Simple on-line implementation

[*Ho and Cao, 1991*, *Glasserman, 1991*, *Cassandras, 1993, 2008*]

REAL-TIME STOCHASTIC OPTIMIZATION: *HYBRID SYSTEMS*



A general framework for an IPA theory in Hybrid Systems

PERFORMANCE OPTIMIZATION AND IPA

Performance metric (objective function):

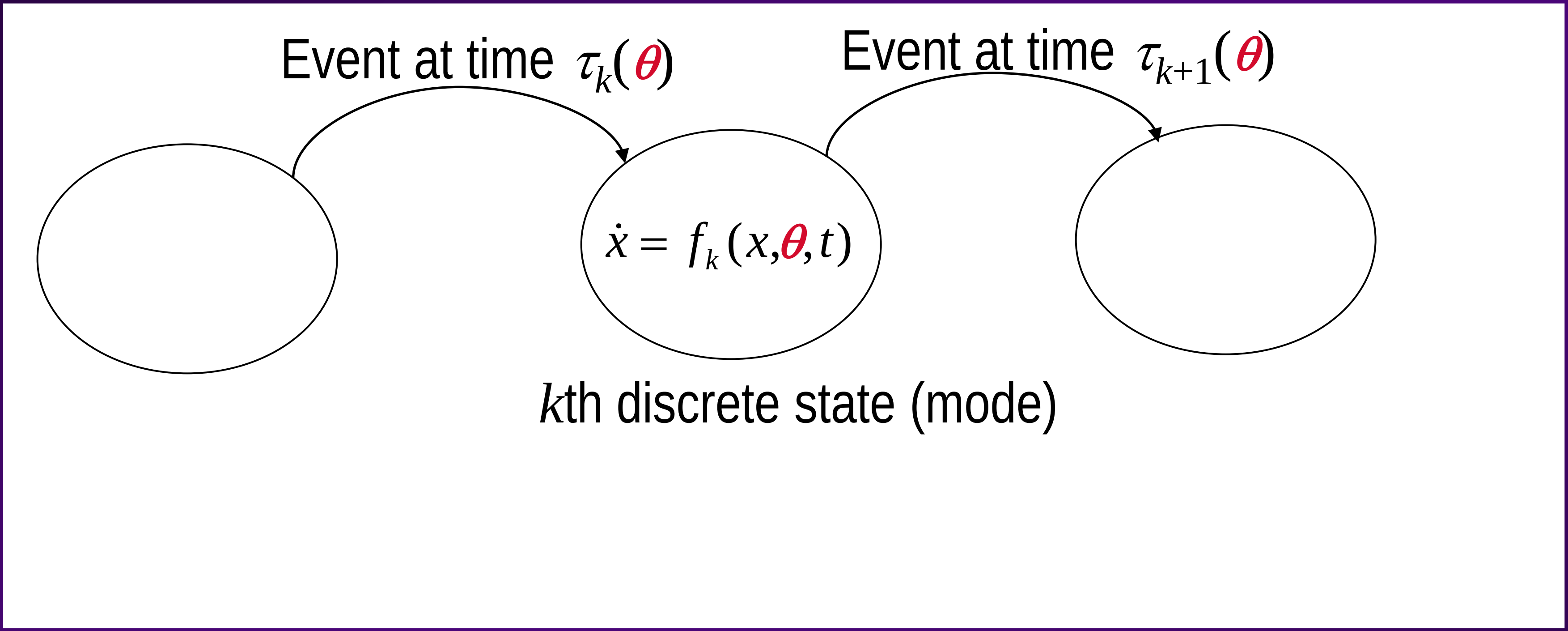
$$J\left(\theta; x(\theta,0), T\right) = E\left[L\left(\theta; x(\theta,0), T\right)\right]$$

IPA goal:

- Obtain unbiased estimates of $\dfrac{dJ\left(\theta; x(\theta,0), T\right)}{d\theta}$, normally $\dfrac{dL(\theta)}{d\theta}$
- Then: $\theta_{n+1} = \theta_n + \eta_n \dfrac{dL(\theta_n)}{d\theta}$

NOTATION: $x'(t) = \dfrac{\partial x(\theta,t)}{\partial \theta}, \quad \tau'_k = \dfrac{d\tau_k(\theta)}{d\theta}$

STOCHASTIC HYBRID AUTOMATA



θ : control parameter, $\theta \in \Theta$ (system design parameter,
parameter of an input process,
or parameter that characterizes a control policy)

THE IPA CALCULUS

IPA: *THREE FUNDAMENTAL EQUATIONS*

System dynamics over $(\tau_k(\theta),\ \tau_{k+1}(\theta)]$: $\dot{x} = f_k(x,\theta,t)$

1. $x'(\tau_k^+) = x'(\tau_k^-) + [f_{k-1}(\tau_k^-) - f_k(\tau_k^+)] \cdot \tau'_k$

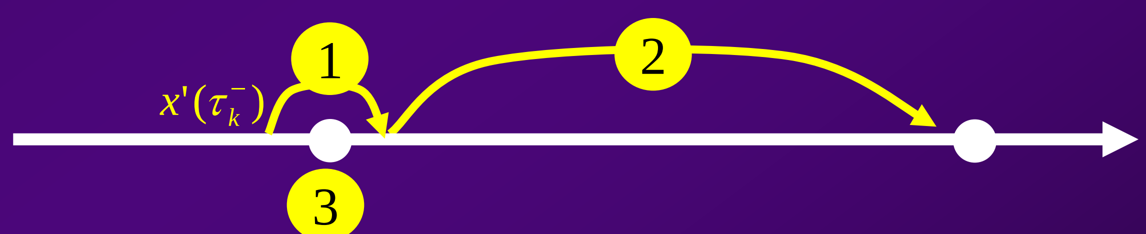
2. $$x'(t) = e^{\int_{\tau_k}^{t} \frac{\partial f_k(u)}{\partial x} du} \left[\int_{\tau_k}^{t} \frac{\partial f_k(v)}{\partial \theta} e^{-\int_{\tau_k}^{v} \frac{\partial f_k(u)}{\partial x} du} dv + x'(\tau_k^+) \right]$$

3. $\tau'_k = 0$ or $$\tau'_k = -\left[\frac{\partial g}{\partial x} f_k(\tau_k^-) \right]^{-1} \left(\frac{\partial g}{\partial \theta} + \frac{\partial g}{\partial x} x'(\tau_k^-) \right)$$

Recall:

$$x'(t) = \frac{\partial x(\theta,t)}{\partial \theta}$$

$$\tau'_k = \frac{d\tau_k(\theta)}{d\theta}$$



Cassandras et al, Europ. J. Control, 2010

IPA PROPERTIES

Back to performance metric: $L(\theta) = \sum_{k=0}^{N} \int_{\tau_k}^{\tau_{k+1}} L_k(x,\theta,t)dt$

NOTATION: $L_k'(x,\theta,t) = \dfrac{\partial L_k(x,\theta,t)}{\partial \theta}$

Then: $$\boxed{\frac{dL(\theta)}{d\theta} = \sum_{k=0}^{N} \Bigg[\underbrace{\tau_{k+1}' \cdot L_k(\tau_{k+1}) - \tau_k' \cdot L_k(\tau_k)}_{\text{What happens at event times}} + \underbrace{\int_{\tau_k}^{\tau_{k+1}} L_k'(x,\theta,t)dt}_{\text{What happens between event times}} \Bigg]}$$

IPA PROPERTIES: *ROBUSTNESS*

THEOREM 1: If either 1,2 holds, then $dL(\theta)/d\theta$ depends only on information available at event times τ_k:

1. $L(x,\theta,t)$ is independent of t over $[\tau_k(\theta), \tau_{k+1}(\theta))$ for all k
2. $L(x,\theta,t)$ is only a function of x and for all t over $[\tau_k(\theta), \tau_{k+1}(\theta))$:

$$\frac{d}{dt}\frac{\partial L_k}{\partial x} = \frac{d}{dt}\frac{\partial f_k}{\partial x} = \frac{d}{dt}\frac{\partial f_k}{\partial \theta} = 0$$

Yao and Cassandras, J. DEDS, 2011

$$\frac{dL(\theta)}{d\theta} = \sum_{k=0}^{N}\left[\tau'_{k+1}\cdot L_k(\tau_{k+1}) - \tau'_k \cdot L_k(\tau_k) + \cancel{\int_{\tau_k}^{\tau_{k+1}} L'_k(x,\theta,t)dt}\right]$$

IMPLICATION: - Performance sensitivities can be obtained from information limited to event times, which is easily observed

- *No need to track system in between events !*

IPA PROPERTIES: *DECOMPOSABILITY*

THEOREM 2: Suppose an endogenous event occurs at τ_k with switching function $g(x,\theta)$.

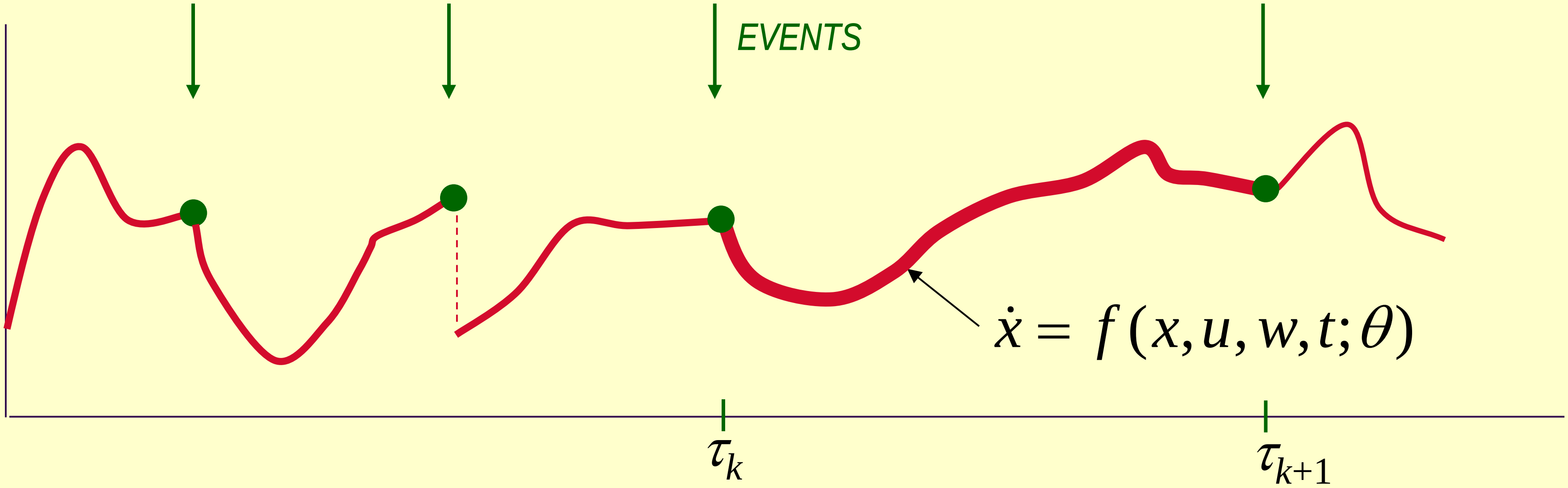
If $f_k(\tau_k^+) = 0$, then $x'(\tau_k^+)$ is independent of f_{k-1}.

If, in addition, $\frac{dg}{d\theta} = 0$ then $x'(\tau_k^+) = 0$

IMPLICATION: Performance sensitivities are often reset to 0

$\Rightarrow$ sample path can be conveniently decomposed

IPA PROPERTIES



Evaluating $x(t;\theta)$ requires full knowledge of w and f values (obvious)

However, $\dfrac{dx(t;\theta)}{d\theta}$ may be *independent* of w and f values (*NOT* obvious)

It often depends only on: - event times τ_k

- possibly $f(\tau_{k+1}^-)$

IPA PROPERTIES: *SCALEABILITY*

OBSERVATION: IPA is *event-driven*

$\Rightarrow$ scales with event set size

1. $x'(\tau_k^+) = x'(\tau_k^-) + [f_{k-1}(\tau_k^-) - f_k(\tau_k^+)] \cdot \tau'_k$

2. $x'(\tau_{k+1}^-) = e^{\int_{\tau_k}^{\tau_{k+1}} \frac{\partial f_k(u)}{\partial x} du} \left[\int_{\tau_k}^{\tau_{k+1}} \frac{\partial f_k(v)}{\partial \theta} e^{-\int_{\tau_k}^{v} \frac{\partial f_k(u)}{\partial x} du} dv + x'(\tau_k^+) \right]$

3. $\tau'_k = 0$ or $\tau'_k = -\left[\frac{\partial g}{\partial x} f_k(\tau_k^-) \right]^{-1} \left(\frac{\partial g}{\partial \theta} + \frac{\partial g}{\partial x} x'(\tau_k^-) \right)$

IPA PROPERTIES

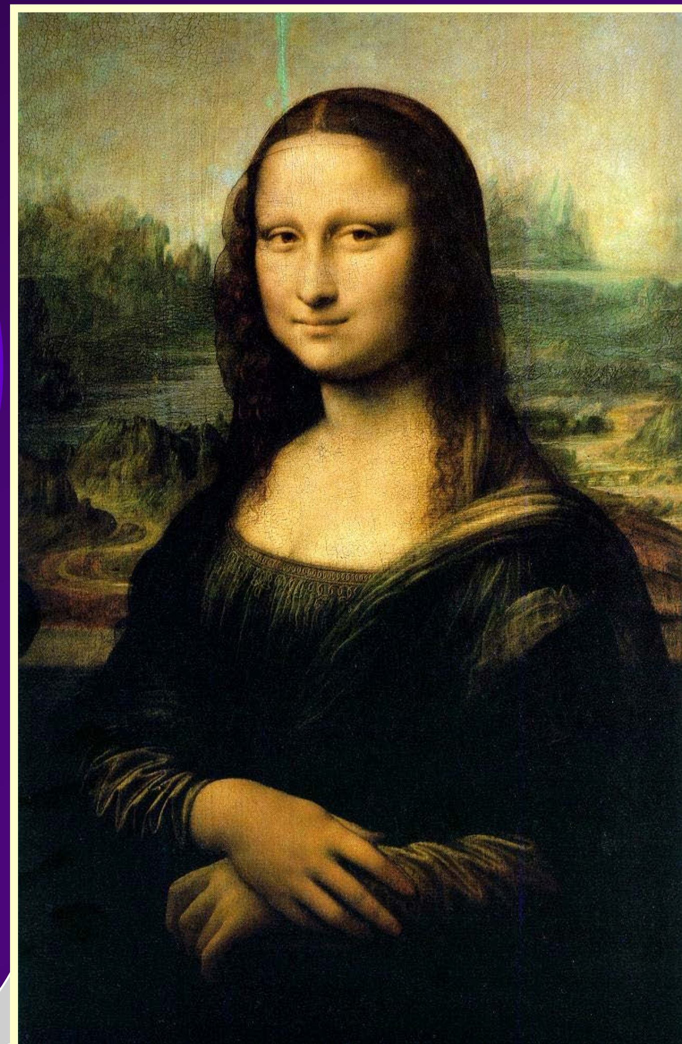
In many cases:

- *No need for a detailed model* (captured by f_k) to describe state behavior in between events

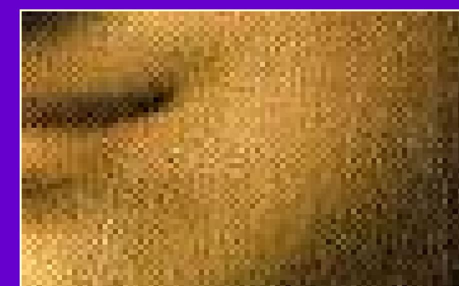
- This explains why *simple abstractions of a complex stochastic system* can be adequate to perform sensitivity analysis and optimization, as long as event times are accurately observed and local system behavior at these event times can also be measured

WHAT IS THE RIGHT ABSTRACTION LEVEL ?

TOO FAR…
model not
detailed enough



JUST RIGHT…
good model



TOO CLOSE…
too much
undesirable
detail

CREDIT: W.B. Gong

ADAPTIVE TRAFFIC LIGHT CONTROL

TRAFFIC LIGHT CONTROL - BACKGROUND

- Mixed Integer Linear Programming (MILP) [*Dujardin et al, 2011*]
- Extended Linear Complementarity Problem (ELCP) [*DeSchutter, 1999*]
- MDP and Reinforcement Learning [*Yu et al., 2006*]
- Game Theory [*Alvarez et al., 2010*]
- Evolutionary algorithms [*Taale et al., 1998*]
- Fuzzy Logic [*Murat et al., 2005*]
- Expert Systems [*Findler and Stapp, 1992*]
- *Perturbation Analysis* [*Panayiotou et al., 2005*]

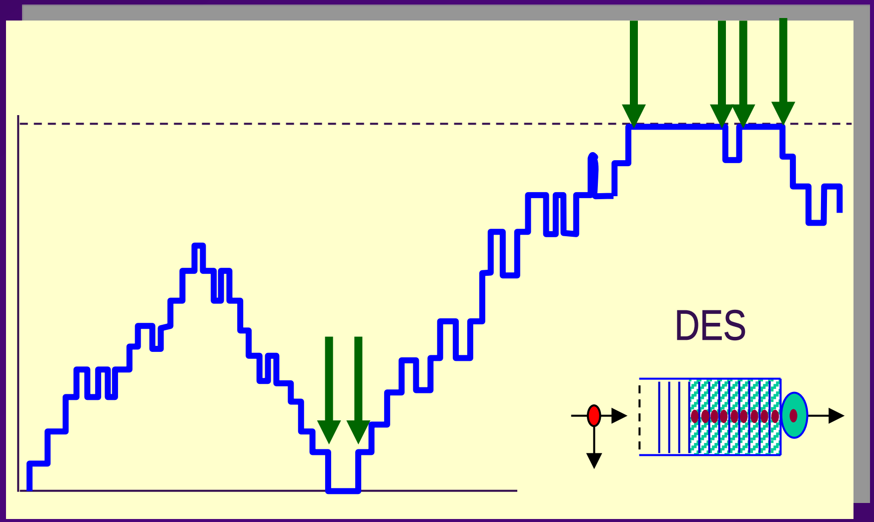
TRAFFIC LIGHT CONTROL - BACKGROUND

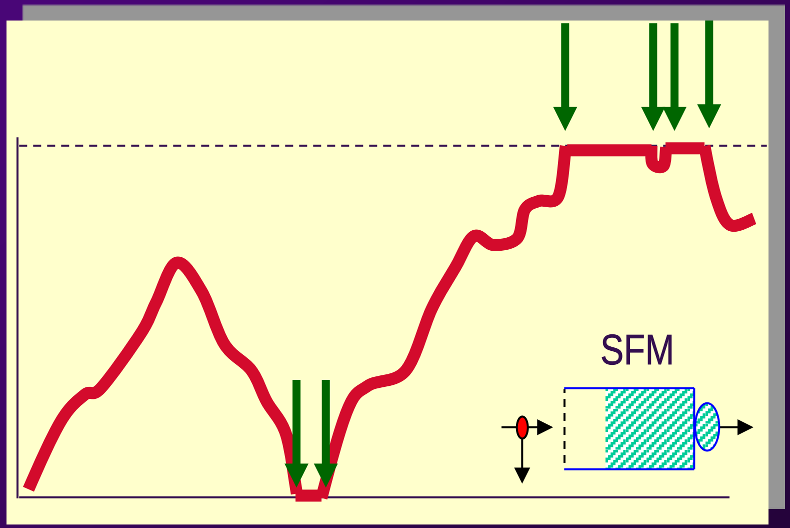
- *Perturbation Analysis* [*Panayiotou et al., 2005*]
  [*Geng and Cassandras, 2012*]

Single Intersection

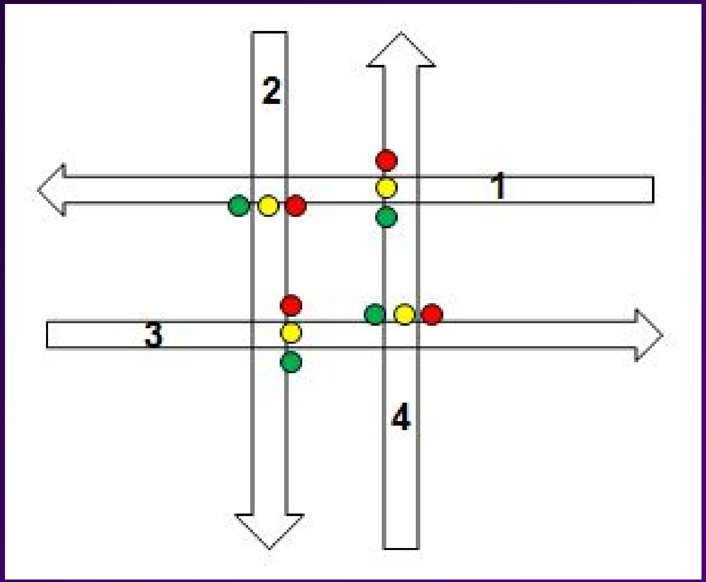
Use a Hybrid System Model: Stochastic Flow Model (SFM):

- Aggregate states into *modes*
- Keep only events causing mode transitions
- In each mode, approximate discrete event behavior by diff. equations





SINGLE-INTERSECTION MODEL



Traffic light control:

$$\theta = [\theta_1, \theta_2, \theta_3, \theta_4]$$

GREEN light cycle
at queue n = **1,2,3,4**

Assumptions:

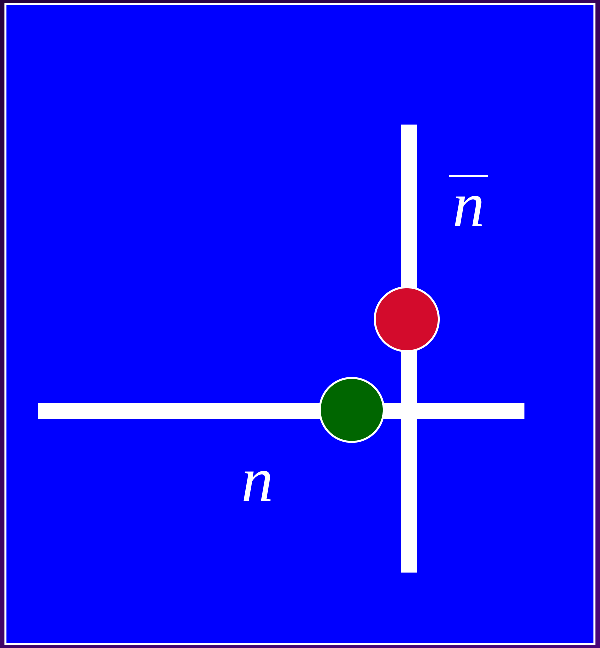
- No left-turn or right-turn
- Yellow light combined with red light

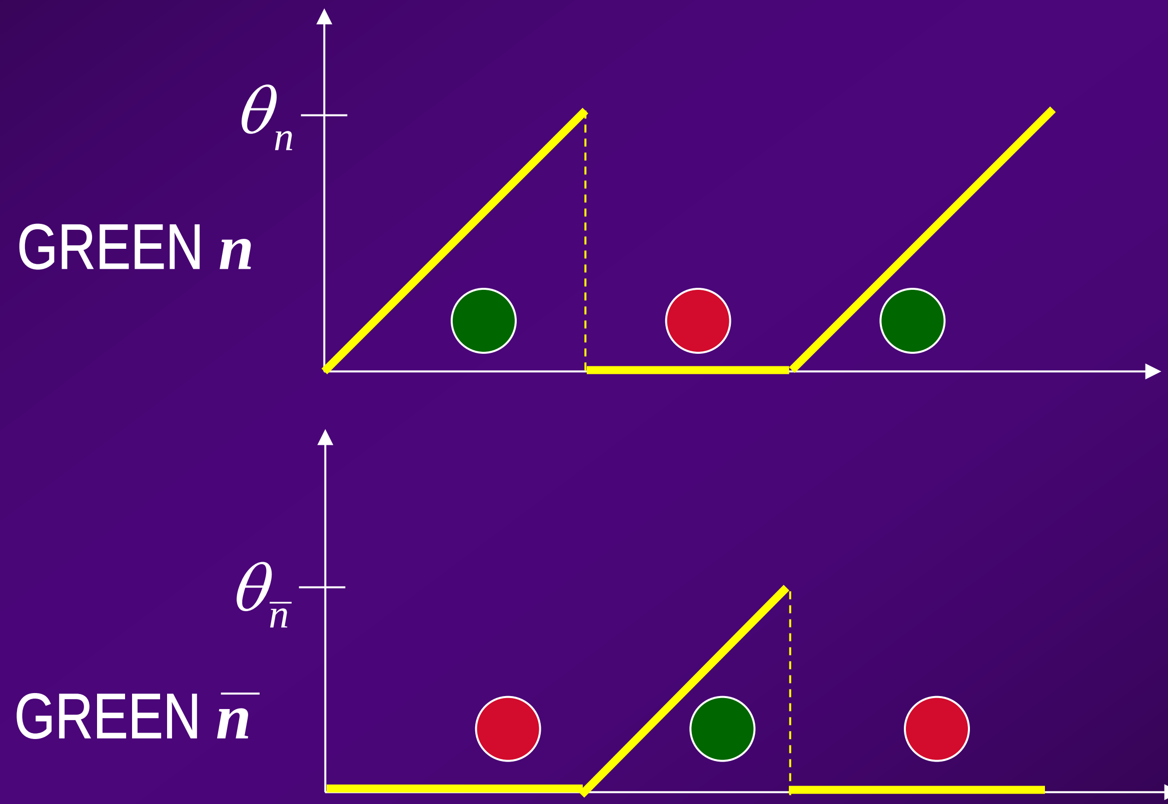
OBLECTIVE: Determine θ to minimize total weighted vehicle queue contents

$$\min_{\theta} \frac{1}{T} \sum_{n=1}^{6} \int_0^T w_n x_n(\theta, t)\, dt$$

EXTENSIONS: - Two intersections with blocking: *Geng and Cassandras, 2013*
- Quasi-dynamic control: *Fleck et al, 2014*

HYBRID SYSTEM STATE DYNAMICS





$$\dot{z}_n(t) = \begin{cases} 1 & if\ \ 0 < z_n(t) < \theta_n \ \ or\ \ z_{\bar{n}}(t) = \theta_{\bar{n}} \\ 0 & otherwise \end{cases}$$

GREEN light "clock"

$$z_n(t^+) = 0 \; if \;\; z_n(t) = \boxed{\theta_n}$$

→ Control variable: GREEN light cycle

HYBRID SYSTEM STATE DYNAMICS

$$\dot{z}_n(t) = \begin{cases} 1 & \text{if } 0 < z_n(t) < \theta_n \text{ or } z_{\bar{n}}(t) = \theta_{\bar{n}} \\ 0 & \text{otherwise} \end{cases}$$

$$z_n(t^+) = 0 \text{ if } z_n(t) = \theta_n$$

Define:

$$G_n(t) = \begin{cases} 1 & \text{if } 0 < z_n(t) < \theta_n \text{ or } z_{\bar{n}}(t) = \theta_{\bar{n}} \\ 0 & \text{otherwise} \end{cases}$$

GREEN ... queue ***n***

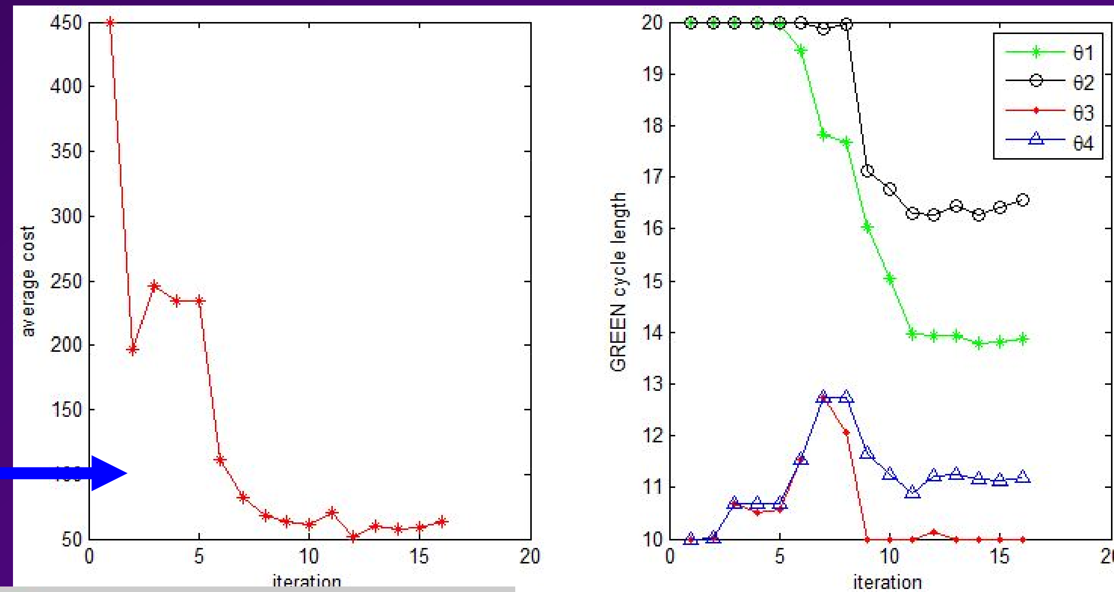
...tent

$$\dot{x}_n(t) = \begin{cases} \alpha_n(t) & \\ 0 & \\ \alpha_n(t) - \beta_n(t) & \text{...wise} \end{cases}$$

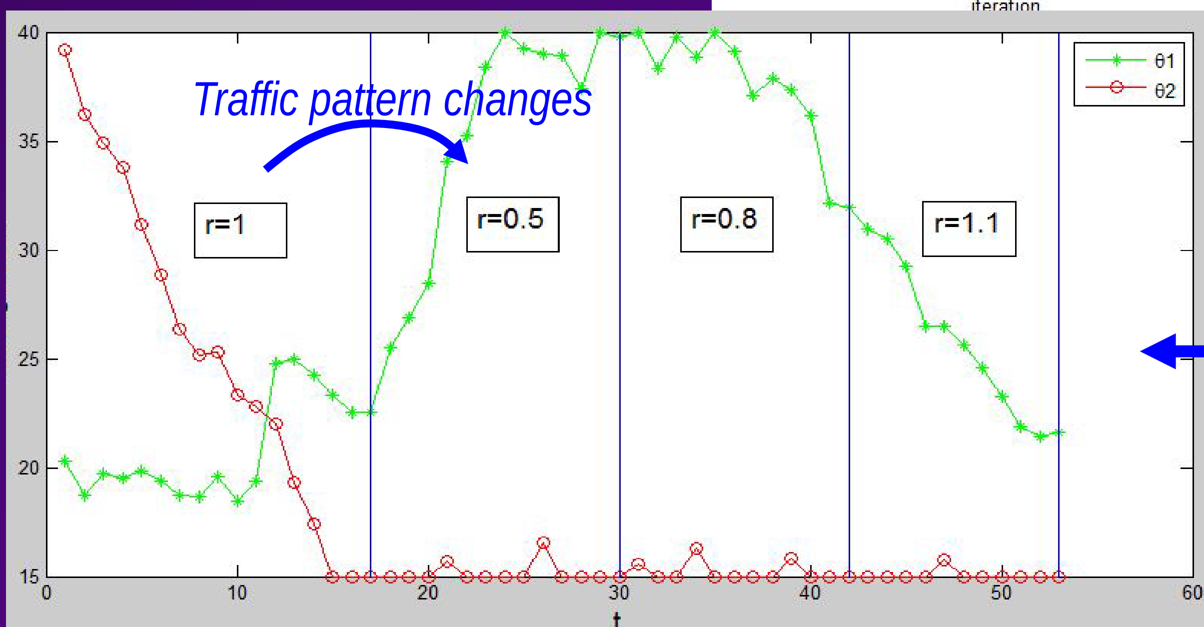
Vehicle departure process

IPA ROBUSTNESS:
$\alpha_n(t)$, $\beta_n(t)$ DO NOT HAVE TO BE KNOWN!

SIMULATION RESULTS

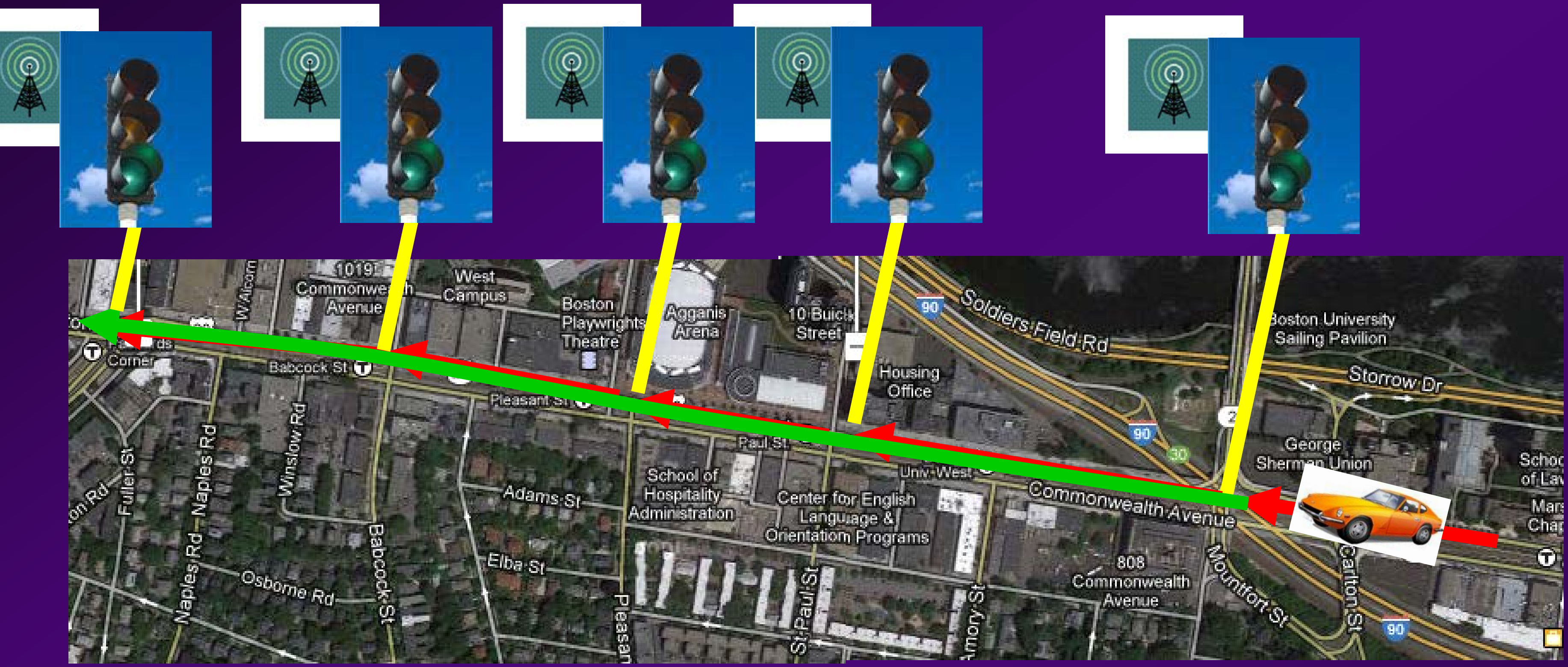


9-fold cost reduction



Adaptivity

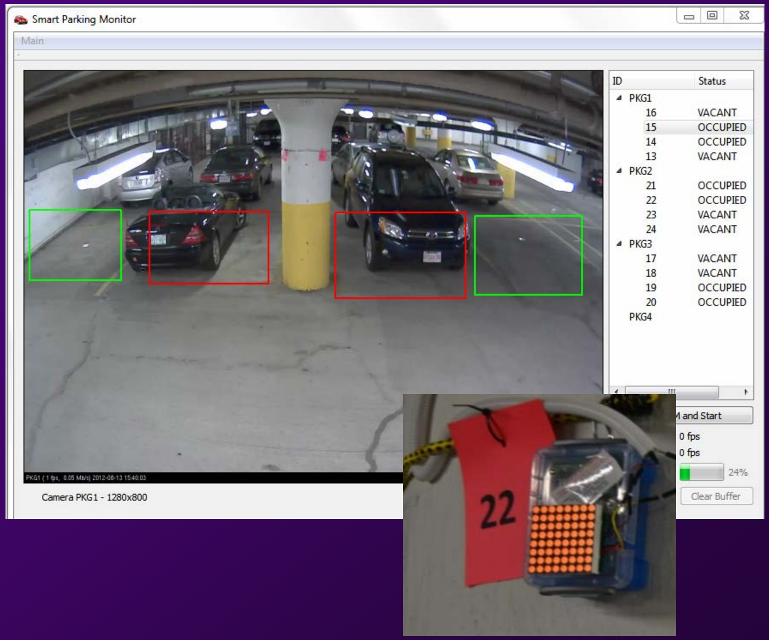
NETWORK-WIDE TRAFFIC LIGHT CONTROL



- Automatically adapt red/green light cycles based on observed data
- Predict and alleviate congestion over entire urban network
- Reduce waiting times, congestion
- Reduce pollution and fuel waste

SMART PARKING

iPhone app



SMART PARKING

***30%* of vehicles on the road in the downtowns of major cities are cruising for a parking spot. It takes the average driver *7.8* minutes to find a parking spot in the downtown core of a major city.**

R. Arnott, T.Rave, R.Schob, *Alleviating Urban Traffic Congestion.* 2005

GUIDANCE-BASED PARKING – DRAWBACKS…

Drivers:

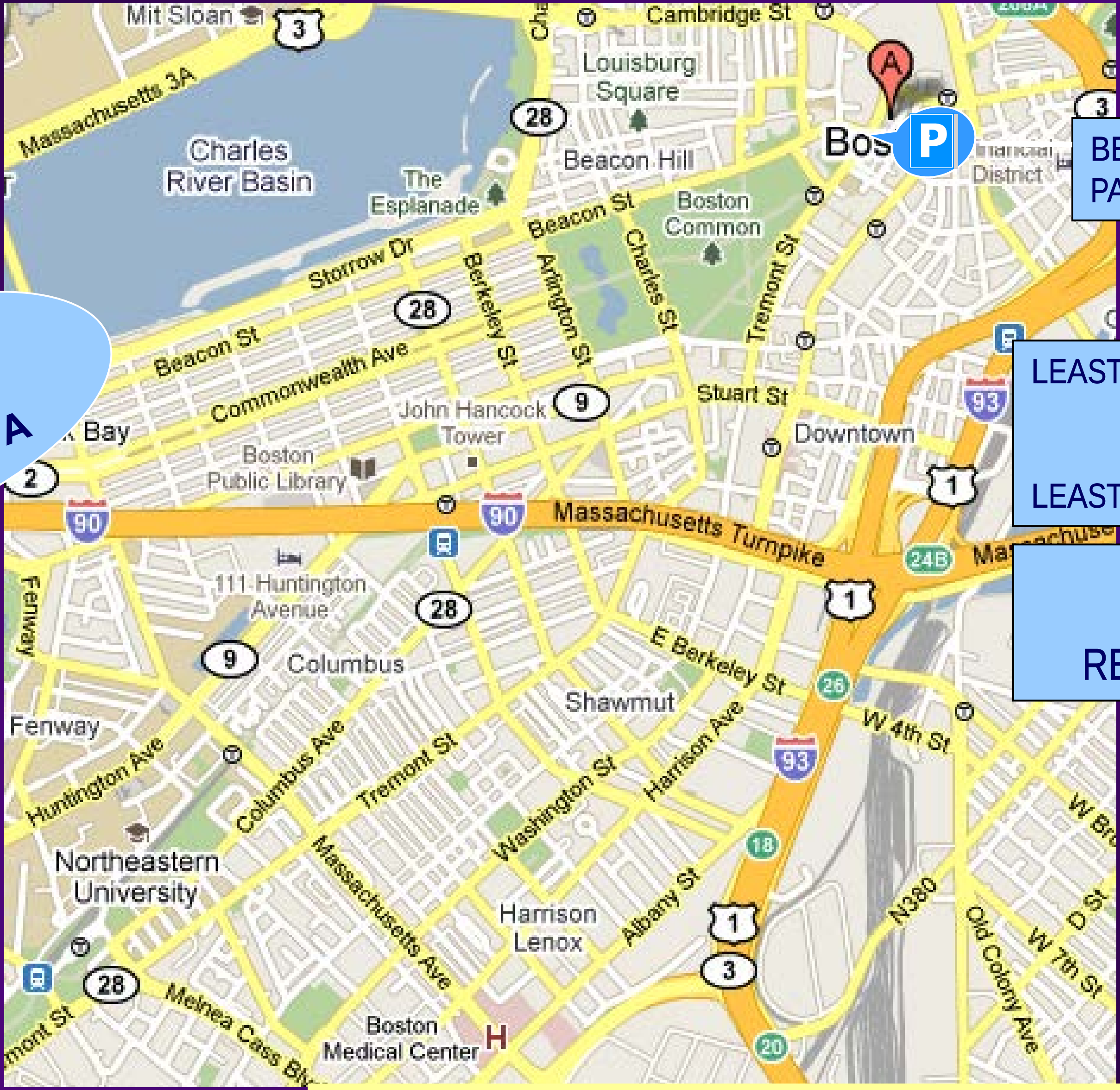
- May not find a vacant space
- May miss better space
- Processing info while driving

City:

- Imbalanced parking utilization
- May create ADDED CONGESTION (as multiple drivers converge to where a space exists)

Searching for parking $\Rightarrow$ Competing for parking

SMART PARKING



Find best parking spot for DESTINATION A

BEST PARKING SPOT

LEAST DISTANCE from A

+

LEAST COST

+

RESERVE IT

[Geng and Cassandras, *IEEE Trans. on Intelligent Transportation Systems*, 2013]

WHAT IS *REALLY* "SMART" ?

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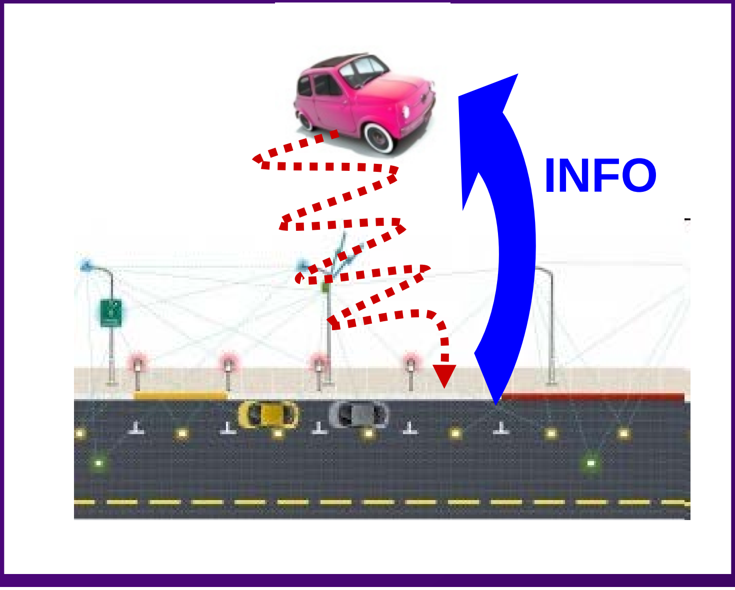
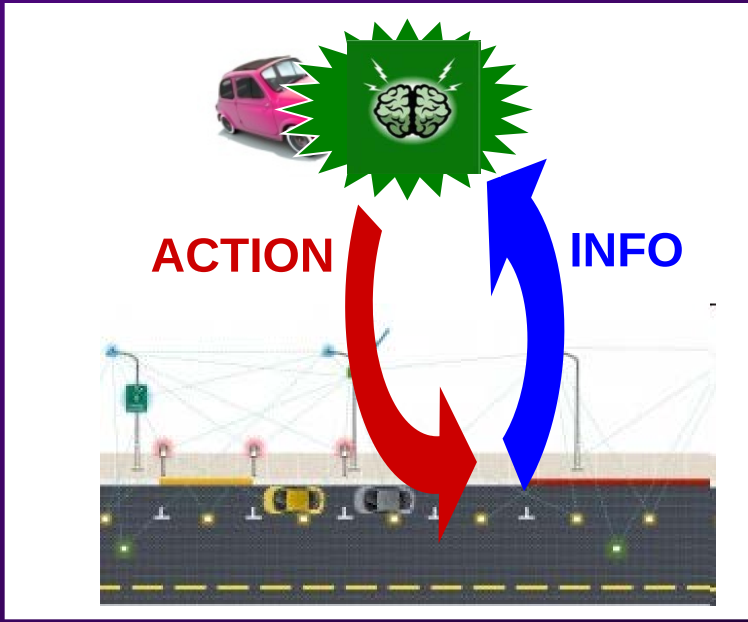
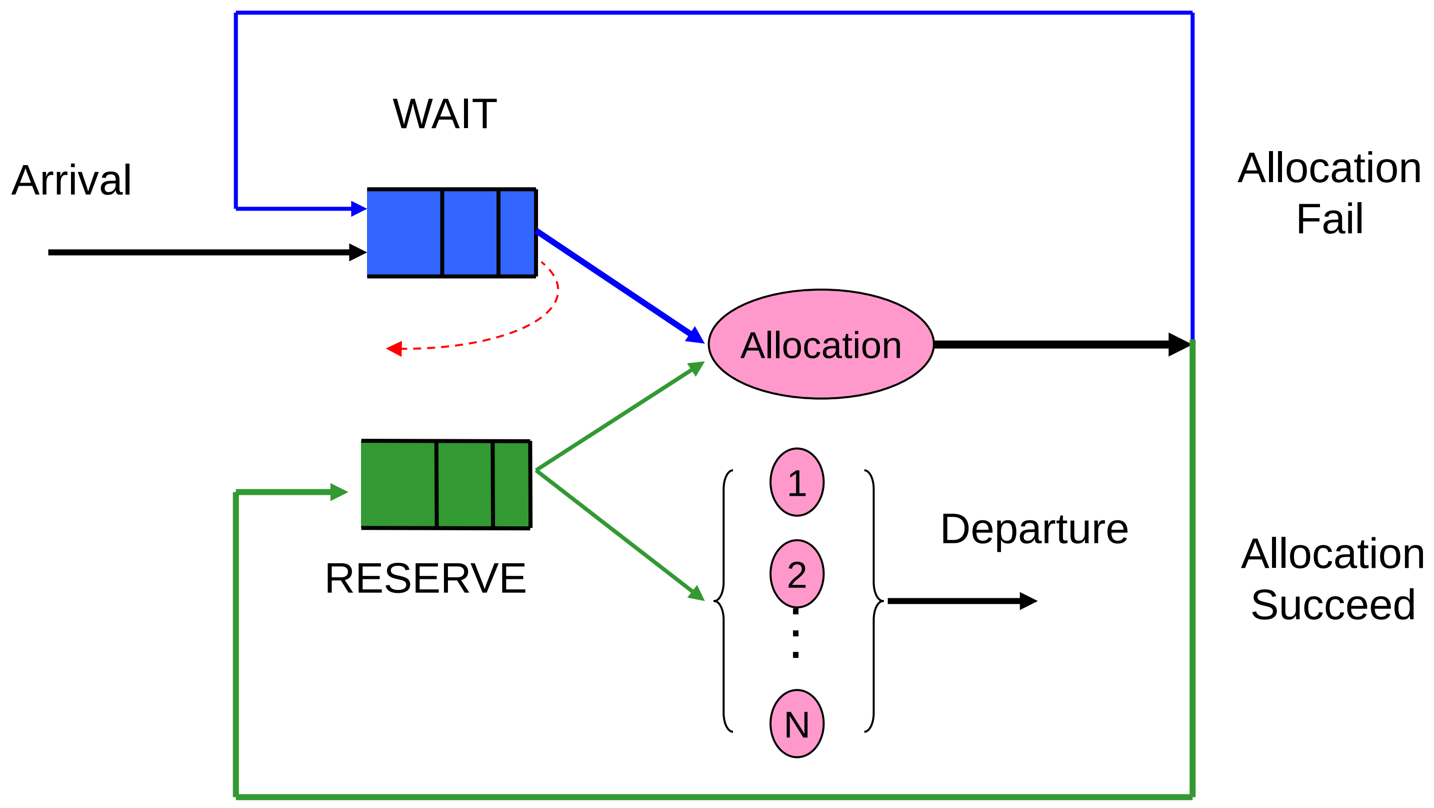
- JUST A NECESSARY STEP TO BEING "SMART"



PROCESSING DATA TO MAKE GOOD DECISIONS IS "SMART"



PROBLEM FORMULATION



MILP FORMULATION

$$\min \sum_{i\in W(k)\cup R(k)} \sum_{j\in\Omega_i(k)} x_{ij}\cdot J_{ij}(k) + \sum_{i\in W(k)} \left(1-\sum_{j\in\Omega_i(k)} x_{ij}\right)$$

s.t.

$$\sum_{i\in W(k)\cup R(k)} x_{ij} \le 1 \quad \forall j\in\Gamma(k)$$

$$\sum_{j\in\Omega_i(k)} x_{ij} \le 1 \quad \forall i\in W(k)$$

$$\sum_{j\in\Omega_i(k)} x_{ij} = 1 \quad \forall i\in R(k)$$

Reservation Guarantee

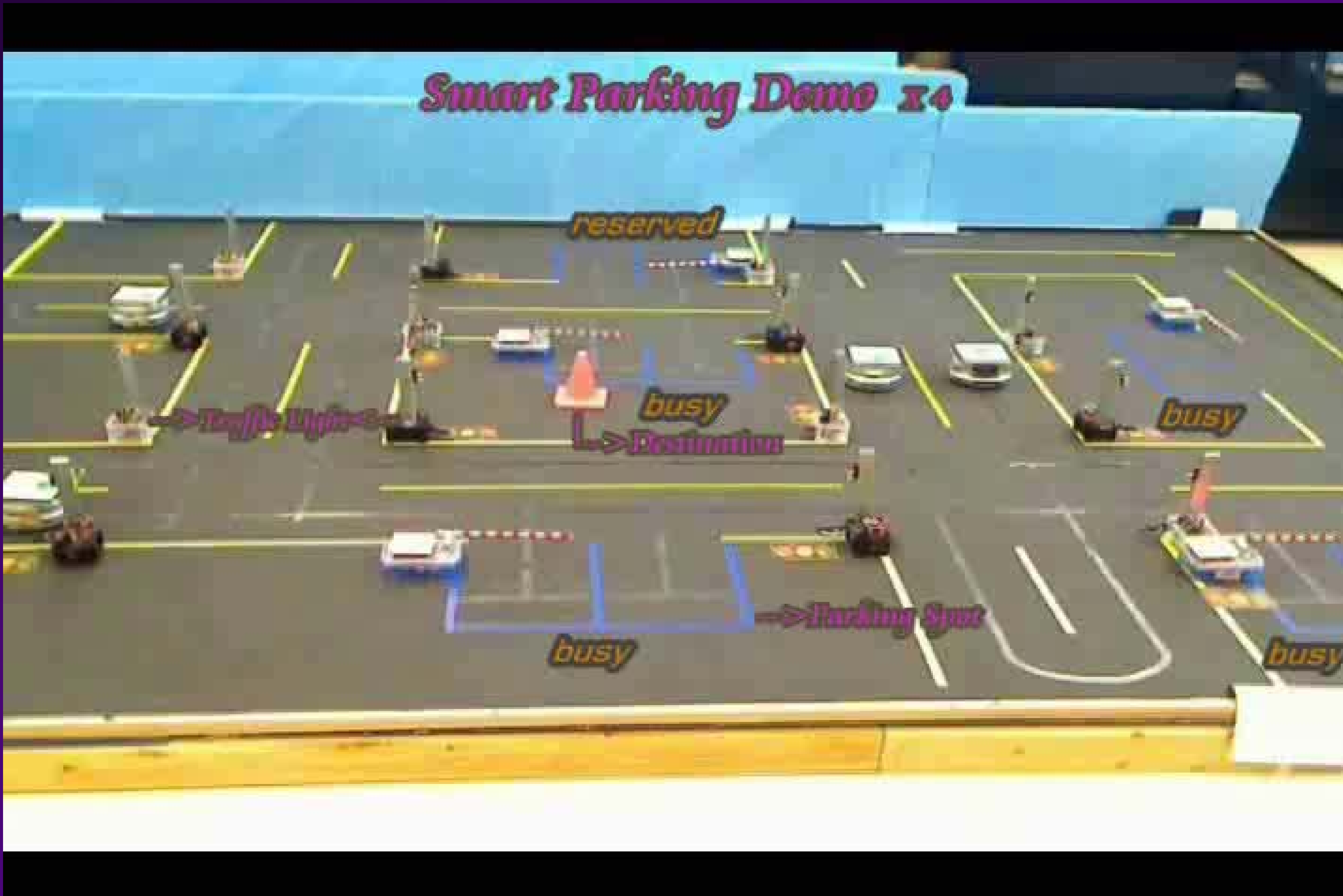
$$\sum_{j\in\Omega_i(k)} x_{ij}\cdot J_{ij}(k) \le J_{iq_i(k-1)}(k) \quad \forall i\in R(k)$$

Reservation Upgrade

$$\left(\sum_{n\in\Omega_i(k)} x_{in}\right) - x_{mj} \ge 0 \quad \forall j\in\Gamma(k), i\in\{i \mid j\in\Omega_i(k)\},$$
$$m\in\{m \mid j\in\Omega_m(k), t_{mj} > t_{ij}, m\in W(k)\}$$

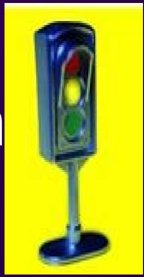
Fairness

$$x_{ij}\in\{0,1\} \quad \forall i\in W(k)\cup R(k),\ j\in\Omega_i(k)$$


Smart Parking Demo x4
reserved
busy
->Destination
busy
busy
->Parking Spot
busy

SMART PARKING – IMPLEMENTATION

- Parking space availability detection
  - Standard sensors (e.g., magnetic, cameras)
  - Wireless sensor networking
- Vehicle localization
  - GPS
- System-Driver communication
  - Smartphone
  - Vehicle navigation system
- Parking reservation
  - Red/Green/Yellow light system



SIMULATION CASE STUDY

On-street parking spaces

Off-street parking spaces

Points of interest

KEY CONCLUSIONS

1. 10-20% higher parking utilization
   $\Rightarrow$ HIGHER REVENUE,
   LOWER CONGESTION

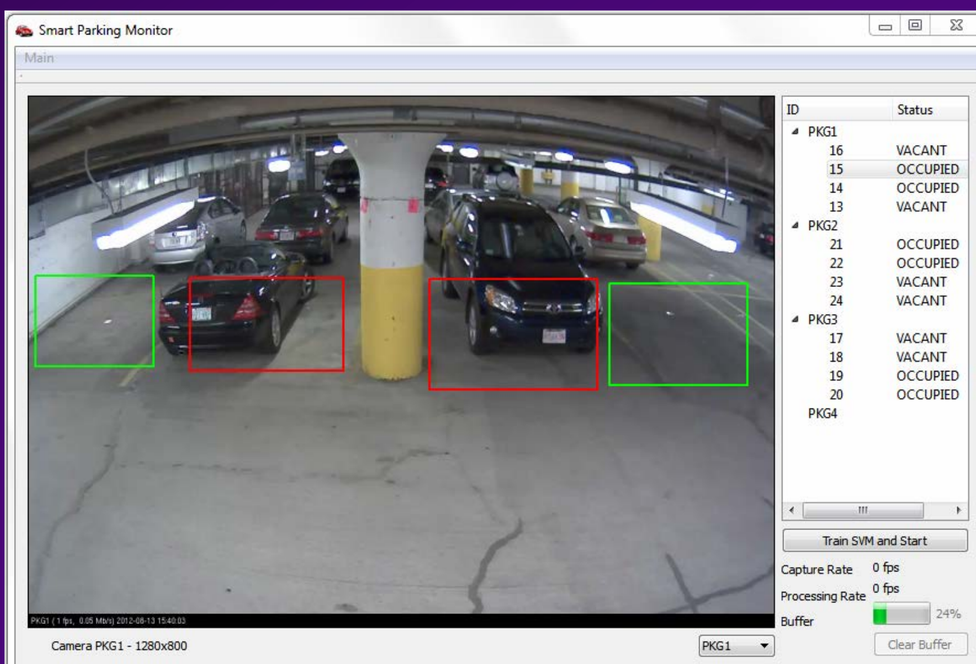
2. % drivers searching for parking (wandering) < 2%
   $\Rightarrow$ HIGHER REVENUE,
   LOWER CONGESTION

3. 50% reduction in parking time under heavy traffic
   $\Rightarrow$ LOWER CONGESTION,
   LESS FUEL,
   DRIVER COMFORT

SMART PARKING - IMPLEMENTATION

2011 IBM/IEEE Smarter Planet Challenge prize

http://smartpark.bu.edu/smartparking_ios6/login.php



Currently in operation at BU garage
(with Smartphone app: *BU Smart Parking*)

http://www.bu.edu/buniverse/view/?v=1zqb6NnD

http://www.necn.com/09/23/11/JoeBattParkingapp/landing_scitech.html?blockID=566574&feedID=4213

STREET BUMP: DETECTING "BUMPS" THROUGH SMARTPHONES + DATA ANALYTICS

iPhone app

2014 IBM/IEEE Smarter Planet Challenge prize

STREET BUMP – PROCESSING "BIG DATA"

- Detect obstacles using iPhone accelerometer and GPS
  ⇒ no infrastructure needed

- Send to central server through Street Bump app

- Process data to classify obstacles:

  Anomaly detection and clustering algorithms,
  similar to cybersecurity problems

- Detect "actionable" obstacles

- Prioritize and dispatch Smart City crews to fix problems:

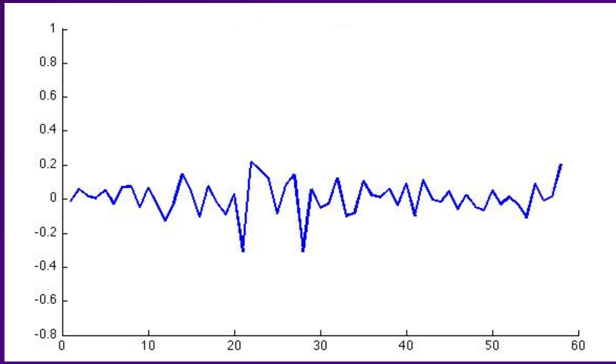
  DATA-DRIVEN DYNAMIC RESOURCE ALLOCATION

[Brisimi et al, *IEEE CASE*, 2015 subm.]

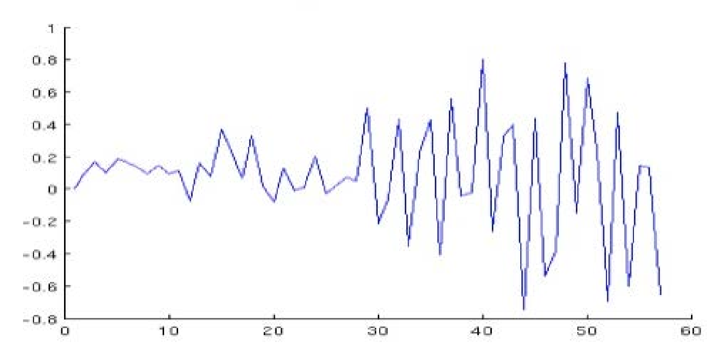
STREET BUMP – PROCESSING "BIG DATA"

Methodologies used:

- Anomaly detection, Machine Learning algorithms
- Bump signal signature analysis: REGULARITY METRIC
- Bump signal randomness content: ENTROPY METRIC



NON-ACTIONABLE
(Flat Casting)



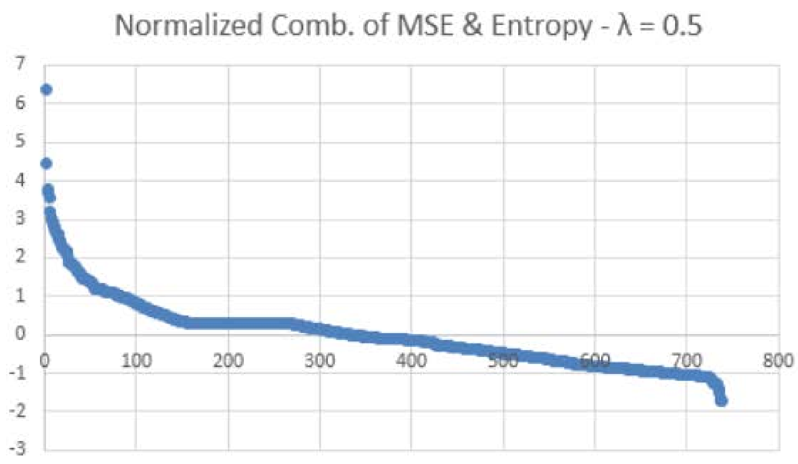
ACTIONABLE
(Pothole)

STREET BUMP – ANOMALY INDEX RANKED LIST

$$AI = 0.5MSE + 0.5H(x)$$

TOP-10 ACTIONABLE OBSTACLES

- $\lambda = 0.5$
- Truly actionable (T): 88/100 (88%)
- False Alarm (F): 12%



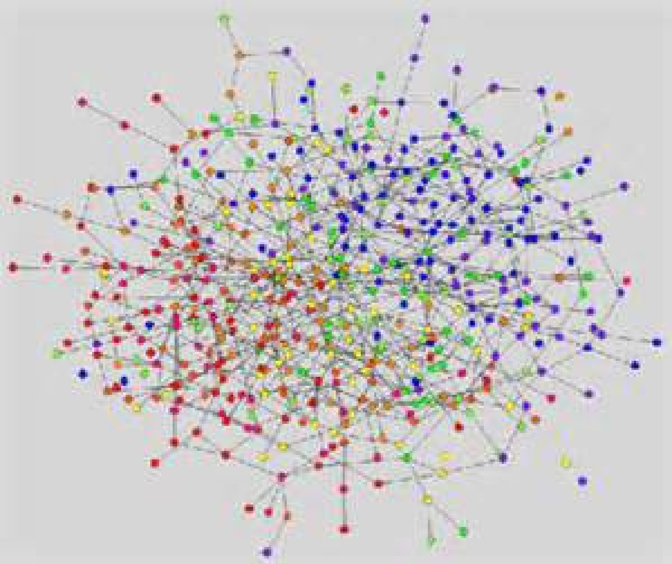
Categories	1 = Non-actionable	Comb. of MSE&Entropy
'Pot Hole'	2	6.358133291
'Sunk Casting (Immediate repair)'	2	4.458249603
'Pothole'	2	3.781396384
'Cracking Around Casting (Pothole)'	2	3.696543324
'Bad Utility Patch (permanent)'	2	3.553264957
'Pothole'	2	3.209940023
'Pothole'	2	3.035801435
'Bad Utility Patch (permanent)'	2	2.963345039
'Flat Casting'	1	2.928413599
'Pothole'	2	2.83604503
'Bad Utility Patch (permanent)'	2	2.783582864
'Sunk Casting (immediate repair)'	2	2.726196475
'Catch Basin (repair)'	2	2.626632962
'Pothole'	2	2.626487835
'Sunk Casting (repair)'	2	2.496122077
'Bad Utility Patch (permanent)'	2	2.441951962
'Pothole'	2	2.393910452
'Sunk Casting (immediate repair)'	2	2.302992173
'Sunk Casting (repair)'	2	2.271229115
'Pot Hole'	2	2.253794862
'Sunk Casting (repair)'	2	2.225175587
'Sunk Casting (immediate repair)'	2	2.204039646
'Cracking Around Casting (pothole)'	2	2.186933029
'Pothole'	2	2.169196119
'Bad Utility Patch (temporary)'	2	2.096893702
'Pothole'	2	1.961382389
'Sunk Casting (repair)'	2	1.876441708
'Flat Casting'	1	1.855250669
'Pot Hole (no repair)'	1	1.83324128
'Bad Utility Patch (permanent)'	2	1.825949708
'Sunk Casting (Repair)'	2	1.815833626
'Pothole'	2	1.772191028
'Sunk Casting (repair)'	2	1.766306302
'Flat Casting'	1	1.747079501
'Sunk Casting (repair)'	2	1.681360281
'Sunk Casting (immediate repair)'	2	1.651942764
'Raised Casting (repair)'	2	1.618505807
'Pothole'	2	1.574023242
'Sunk Casting (immediate repair)'	2	1.574015672
'Pothole'	2	1.497205598
'Pot Hole'	2	1.484528469
'Pothole'	2	1.469825022
'Catch Basin (repair)'	2	1.462558728
'Sunk Casting (repair)'	2	1.454257109
'Pothole'	2	1.453174152
'Flat Casting'	1	1.422754809
'Sunk Casting (repair)'	2	1.417971776
'Pothole'	2	1.402428087
'Catch Basin (repair)'	2	1.37466431

TRAFFIC CONTROL

The BU Bridge mess, Boston, MA (simulation using VISSIM)

WHY CAN'T WE IMPROVE TRAFFIC…

… EVEN IF WE KNOW THE ACHIEVABLE OPTIMUM IN A TRAFFIC NETWORK ???



Because:

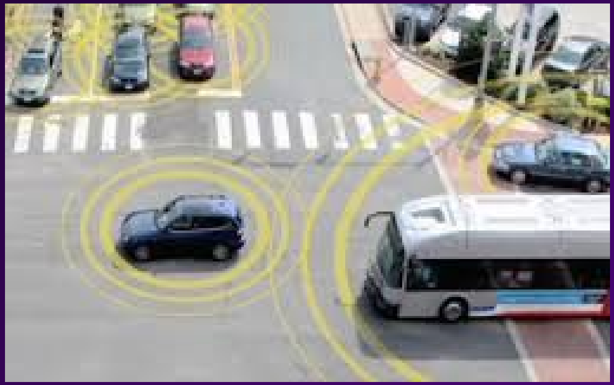
- Not enough controls (traffic lights, tolls, speed fines)

  → No chance to use feedback

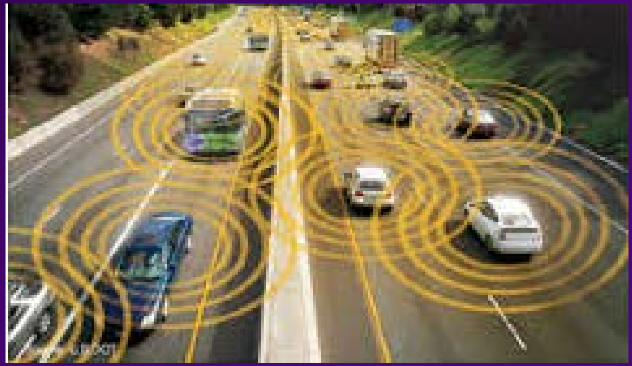
- Not knowing other drivers' behavior leads to poor decisions (a simple game-theoretic fact)

  → Drivers seek individual (selfish) optimum, not system-wide (social) optimum

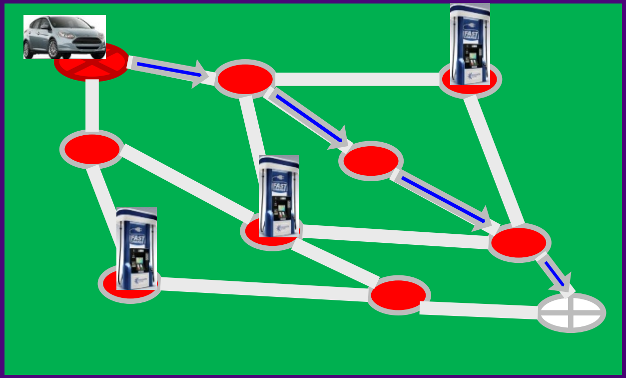
GAME-CHANGING OPPORTUNITY: "CONNECTED VEHICLE" TECHNOLOGY



NO TRAFFIC LIGHTS, NEVER STOP...



FROM (SELFISH) "DRIVER OPTIMAL" TO "SYSTEM OPTIMAL" TRAFFIC CONTROL



OPTIMALLY ROUTE EVs TO MINIMIZE TRAVEL TIMES

+ FIND OPTIMAL CHARGING STATION

+ RESERVE IT

CONCLUSIONS

- "Smart Cities" are complex CYBER-PHYSICAL systems that can be studied in a stochastic hybrid system setting

- Capitalize on WIRELESS NETWORKING + BIG DATA

  + DATA-DRIVEN CONTROL and OPTIMIZATION METHODS

- "CONNECTED VEHICLES" provide a tremendous opportunity for feedback methods,
  game theoretic approaches, no infrastructure

- What about HUMANS? Need to expand to

  CYBER-PHYSICAL *SOCIAL* systems (CPSS)

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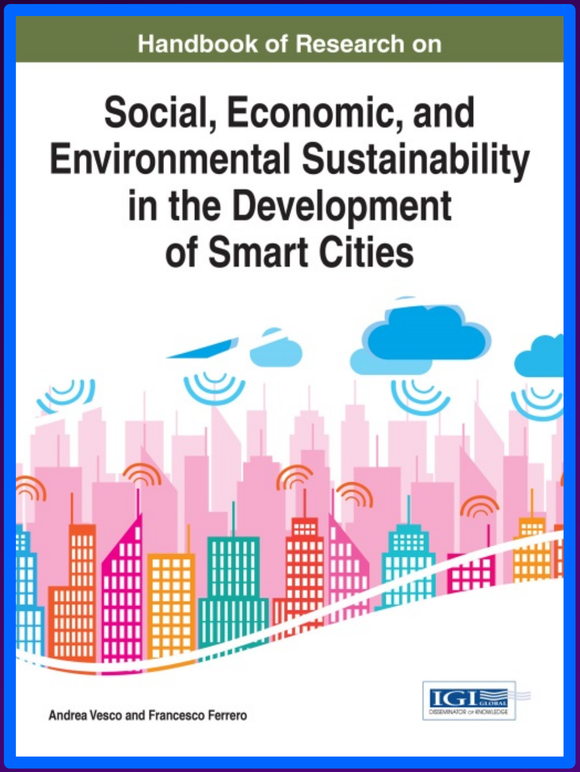

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Thank you